# Find Your Organization in MMORPGs

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IEEE Transactions on Games (Volume: 14, Issue: 3, September 2022)

I read this paper, "Find Your Organisation in MMORPGs".

### Purpose

Modeling the affiliation relationship between players and guilds in MMORPGs

In this article, they aimed to model the affiliation relationship between players and guilds in MMORPGs.



For example, this shows the social structure in MMORPGs. This black line shows the friendship between players. This coloured area shows the membership between players and guilds. It means this blue player is a member of C. In this figure, they want to know which of three guilds A, B, and C matches player u best. Technically, it is considered the matching relationship between players and guilds as a recommendation problem, and formalise it as a link prediction problem on the social. The certain component is a graph convolutional network. For each players in the game, this neural network is trained to estimate the likelihood of wether the player matches the guild.



This could reduce the trial-and-error social cost for players to join a guild blindly. It means this could reduce the time of making human relations, such as establishing contact with other members of the guilds. For the reason why this is important, there are two things. One of them is this. This shows the distribution of the number of guilds the player has stayed for a period of time. This shows that more than 20% of players have stayed in more than three different guilds.



Also, this shows the distribution of different attributes for a single game server. The guild type means the overall impression of the guild, such as fighting, social, casual, and so on. There are many kinds of guilds. Therefore, this system is important for reducing the players' trouble.



Next, I will talk about dataset. They collected players and guilds data from the MMORPG Justice Online. Players' behaviour data are extensively tracked by the game server. The collected game data could be divided into feature data and relationship data.

Dataset

Basic Portrait Gameplay Preference Playtime Preference Player Tags and Guild Tags

First, feature data contains basic portrait, gameplay preference, playtime preference, and player tags and guild tags.



Basic portrait is basic player portraits, such as player level, role, and so on, and basic guild portrait like guild type, guild level, and so on. Gameplay preference is what types of gameplay the player like. This shows the different gameplay preference of ten players in the game. This indicates the significant differences between individual players.



Playtime preference is when players usually play game. They divided the day into fifteen minutes intervals. Then, this shows the different playtime preference of ten players in the game. Some player like to play the game from 7 to 9 a.m., while some player prefer late at night.

Dataset								
	Description							
Name	Meaning							
Highly active	Participate in guild activities and leagues more than a certain number of times per week							
High combat power	The combat ability value ranks in the top positions in the whole server							
High fund contribution	Contribute more than a certain amount of funds (in-game currency assets) to the guild every week							
Enthusiastic captain	Served as the captain of daily quests more than a certain number of times per week							
Scalping master Complete transactional tasks more than a certain number of times per week								
Good atmosphere	Strong atmosphere of chat and social gameplay among guild members							
Frequent activities	More than a certain number of guild activities per week							
Generous rewards	More than a certain number of bounty tasks within the guild per week							
Have friends	More than a certain number of friends are in the guild							
Powerful guild	The league ranking of the guild is high in the whole server							
	Name Highly active High combat power High fund contribution Enthusiastic captain Scalping master Good atmosphere Frequent activities Generous rewards Have friends Powerful mild							

Player tags and guild tags are characteristics of them. These are several representative tags.



Second, relationship data is divided into membership and friendship. Membership shows the player is a member of the guild once, or now. Friendship shows the player is a friend of another player. It could be represented by a simple graph. Nodes are player, numbers represent guild ID, and lines represent friendship. (a) shows that the guild of this player's friends is distributed in several. However, in (b), most of them are concentrated in the guild 11. From this, friendships between players has a great influence on the choice of players' guild. Instead of processing these two graphs separately,



They combined them together to build a heterogeneous graph like this. On the basis of the original friendship network, if the player recently joined the guild, they add a virtual node for each guild, and connect an edge between the player node and the guild node. Then, that player may joined several guild for a period of time.



This is the overall model architecture of neural network model for guild recommendation. The embedding representation of players and guilds are refined with multiple graph propagation layers. Outputs of this are concatenated to make the final link prediction.

Result										
Server	# of players	# of guilds	# of P-G pairs <sup>a</sup>	# of P-P pairs <sup>b</sup>						
1	26,895	431	27,097	488,025						
2	73,639	1,010	75,099	285,049						
3	84,545	1,263	85,773	328,736						

<sup>a</sup>Number of player-guild interaction pairs. <sup>b</sup>Number of player-player interaction pairs.

Result. They have run extensive offline and online evaluation. About offline. Considering that the game process of each game server is different, their recommendation model is server-dependent. They collected the data of three representative game servers for the whole year, from January 1, 2019 to December 31, 2019, to evaluate the effectiveness of their model. The detailed data statistics of these server is this. The first sever is a relatively old one, and others are newly opened and growing servers.



They make the first k guild behaviours of each player as the context to predict (k + 1)th guild behaviour in the training data and validation data.

Result Logic regression MLP Decision tree Random forest XGBoost GCN

They compared the proposed model with several baselines. Logistic regression, this is a linear classification model. MLP, this is a multilayer feed-forward neural network with the nonlinear activation function(ReLU) for each neutron. Decision tree, this is the decision tree learning model. Random forest, this is an ensemble learning method. It combines the bagging sampling and random selection of features to alleviate overfitting. XGBoost, this is an optimised gradient boosting framework for decision trees. GCN, this model only consider the player-guild interaction graph and does not include the player-player friendship graph. This model is used for comparing, and verifying the advantages of friendship relation for guild recommendation.

## Result

#### HR (hit ratio)

#### MRR (mean reciprocal rank)

NDCG (normalized discounted cumulative gain)

For evaluation Metrics, as they focus on recommendation top-N guilds for each player, they used hit ratio, mean reciprocal rank, and normalised discounted cumulative gain to evaluate the system. HR measures the number of guilds that the player is interested in the test data that has been successfully predicted in the top-N ranking list. MRR consider the rank position of the first relevant guild for the player in the ranking list. NDCG measures the usefulness of a guild based on its position in the ranking list, and additionally consider the discount factor at lower ranks.

	Result												
Server 1		Server 2			Server 3								
HR@5	MRR@5	NDCG@5	HR@5	MRR@5	NDCG@5	HR@5	MRR@5	NDCG@5					
0.1571	0.0959	0.1344	0.0733	0.0343	0.0438	0.0399	0.0212	0.0259					
0.1473	0.1013	0.1068	0.0846	0.0424	0.0529	0.0332	0.0183	0.0220					
0.1492	0.0946	0.1080	0.0705	0.0322	0.0416	0.0352	0.0165	0.0211					
0.1111	0.0640	0.0756	0.0860	0.0455	0.0555	0.0366	0.0182	0.0227					
0.1206	0.0624	0.0765	0.0790	0.0354	0.0460	0.0406	0.0219	0.0265					
0.0808	0.0682	0.0671	0.2453	0.1667	0.1856	0.1120	0.0466	0.0627					
0.2290	0.1472	0.1676	0.3304	0.2231	0.2501	0.1294	0.0535	0.0689					
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	HR@5 0.1571 0.1473 0.1492 0.1111 0.1206 0.0808 0.2290	Server 1   HR@5 MRR@5   0.1571 0.0959   0.1473 0.1013   0.1492 0.0946   0.1111 0.0640   0.1206 0.0624   0.0808 0.0682   0.2290 0.1472	Server 1   HR@5 MRR@5 NDCG@5   0.1571 0.0959 0.1344   0.1473 0.1013 0.1068   0.1492 0.0946 0.1080   0.1111 0.0640 0.0756   0.1206 0.0624 0.0765   0.0808 0.0682 0.0671   0.2290 0.1472 0.1676	Server 1   HR@5 MRR@5 NDCG@5 HR@5   0.1571 0.0959 0.1344 0.0733   0.1473 0.1013 0.1068 0.0846   0.1492 0.0946 0.1080 0.0705   0.1111 0.0640 0.0756 0.0860   0.1206 0.0624 0.0765 0.0790   0.0808 0.0682 0.0671 0.2453   0.2290 0.1472 0.1676 0.3304	Server 1 Server 2   HR@5 MRR@5 NDCG@5 HR@5 MRR@5   0.1571 0.0959 0.1344 0.0733 0.0343   0.1473 0.1013 0.1068 0.0846 0.0424   0.1492 0.0946 0.1080 0.0705 0.0322   0.1111 0.0640 0.0756 0.0860 0.0455   0.1206 0.0624 0.0765 0.0790 0.0354   0.0808 0.0682 0.0671 0.2453 0.1667   0.2290 0.1472 0.1676 0.3304 0.2231	Server 1 Server 2   HR@5 MRR@5 NDCG@5 HR@5 MRR@5 NDCG@5   0.1571 0.0959 0.1344 0.0733 0.0343 0.0438   0.1473 0.1013 0.1068 0.0846 0.0424 0.0529   0.1492 0.0946 0.1080 0.0705 0.0322 0.0416   0.1111 0.0640 0.0756 0.0860 0.0455 0.0555   0.1206 0.0624 0.0765 0.0790 0.0354 0.0460   0.0808 0.0682 0.0671 0.2453 0.1667 0.1856   0.2290 0.1472 0.1676 0.3304 0.2231 0.2501	Server 1 Server 2   HR@5 MRR@5 NDCG@5 HR@5 MRR@5 NDCG@5 HR@5   0.1571 0.0959 0.1344 0.0733 0.0343 0.0438 0.0399   0.1473 0.1013 0.1068 0.0846 0.0424 0.0529 0.0332   0.1492 0.0946 0.1080 0.0705 0.0322 0.0416 0.0352   0.1111 0.0640 0.0756 0.0860 0.0455 0.0555 0.0366   0.1206 0.0624 0.0765 0.0790 0.0354 0.0460 0.0406   0.0808 0.0682 0.0671 0.2453 0.1667 0.1856 0.1120   0.2290 0.1472 0.1676 0.3304 0.2231 0.2501 0.1294	Server 1 Server 2 Server 3   HR@5 MRR@5 NDCG@5 HR@5 MRR@5 NDCG@5 HR@5 MRR@5   0.1571 0.0959 0.1344 0.0733 0.0343 0.0438 0.0399 0.0212   0.1473 0.1013 0.1068 0.0846 0.0424 0.0529 0.0332 0.0183   0.1492 0.0946 0.1080 0.0705 0.0322 0.0416 0.0352 0.0165   0.1111 0.0640 0.0756 0.0860 0.0455 0.0555 0.0366 0.0182   0.1206 0.0624 0.0765 0.0790 0.0354 0.0460 0.0219   0.0808 0.0682 0.0671 0.2453 0.1667 0.1856 0.1120 0.0466   0.2290 0.1472 0.1676 0.3304 0.2231 0.2501 0.1294 0.0535					

This is result of offline. Bold number is best method. Underline is second best method. This shows that the proposed model, GuildNet outperformed others. Also, conventional machine learning method, such us LR and XGB, perform worse than GCN-based method. Especially, the comparison between the GCN and GuildNet model highlights the effectiveness of social relationships between players in improving the performance of guild recommendation. In addition, especially on newly opened servers, the GCN-based method consistently outperform other baselines. From this, the propagation of relationships between players on newly opened servers is very important. Furthermore, on the mature server, simple machine learning methods can also achieve good results. It is considered that the gradual stability of player preferences and guild attributes, whereas the influence of relationships is reduced.



In case of online, they compared the proposed GuildNet method and original method. The original method is designed with a heuristic rule based on the game level of players. Then, they randomly distributed recommendation requests to two channels. This is the graphical user interface of the guild recommendation system.



After the system was launched, they collected the online feedback data of a server. This shows that the launch of the model yielded significant gains on application rate, and acceptance rate. However, just the pure fact that a guild has let somebody in may not be a proof that the new member suits the guild well. In order to verify the effectiveness of the guild recommendation system, they have collected the engagement measures of player after entering the guild for a period of time. They selected three indicators to measure after joining the guild.



One of them is guild chat. This measure indicates the player's willingness to communicate with other guild members. Other is guild activity. This measure indicates the player's willingness to participate in the daily activity of the guild. Another is guild league. This measure indicates the player's willingness to collaborate within the guild when competing with other guilds.



This shows the comparison results of degree of engagement. Overall, the proposed recommendation model outperforms the heuristic rules in all involved metrics. These results verified the feasibility and effectiveness of the method in practical applications. Also, proper use of the friend relationship between players can improve the performance of the recommendation system.

# Thank you for listening.